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The Impact of AI Governance on the Financial Reporting Quality: Sustainable Dimensions

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Abstract: The study aims to investigate the role of artificial intelligence (AI) governance on financial reporting quality (FRQ), exploring how various governance mechanisms influence sustainable corporate behavior in the Gulf Cooperation Council (GCC) region. The study employs the quantitative research method of multiple regression analysis (the study uses a dataset of 18,560 firm-year observations of publicly listed companies from the GCC region), exploring how dimensions of AI governance (ethical compliance, data transparency, regulatory compliance) relate to financial reporting quality and firms' sustainability. The study provides evidence of a statistically significant, positive relationship between robust AI governance and higher levels of financial reporting quality, supporting the notion that organizations with strong measurements of AI governance are more likely to produce financial disclosures of appropriate transparency, accuracy, and reliability that could support long-term sustainability. The results of this research provide new evidence for organizational actors (leaders, regulators, policymakers) to strengthen financial transparency, potentially leading to sustainable development, though evidence of enhanced stewardship of the AI process under consideration serves only as an important first step toward supporting productive, sustained engagement with AI-enhanced corporate performance. Finally, this study provides one of the first empirical investigations linking AI governance to financial reporting quality within the GCC context. By using a large-scale dataset, it offers robust evidence on how responsible AI integration can strengthen corporate accountability, improve reporting practices, and support sustainable economic growth.

Keywords: AI governance, Financial reporting quality, Sustainability, Corporate accountability, Gulf Cooperation Council.

1. Introduction

In the last few years, artificial intelligence (AI) has emerged as a significant disruptor to many of the techniques and methods that make up our business operations. This is particularly true in business-relevant areas such as financial reporting, tax compliance, and corporate governance. AI technologies bring improvements in efficiency, availability of credible evidence, accuracy of estimates, and ways of ultimately making decisions within the organization's infrastructure. The increased use of AI brings, therefore, unique challenges associated with ethical accountability, transparency, and complying with regulations. The important elements of AI accountability bring to the fore key factors in AI governance systems for responsible AI use connected to compliant, sustainable management policies. Financial reporting quality (FRQ) is one area of corporate accountability that focuses on and connects managers to accountable relationships with owners and stakeholders, where the importance of FRQ is relevant

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to the impacts of integrating AI. FRQ increases the level of trust an investor has in the reporting entity and deepens opportunities for moving toward a long-term value generation, which, on a larger scale, contributes to the long-term sustainable development of economies.

This research assessed the impact of AI governance on financial reporting quality in the Gulf Cooperation Council (GCC) region. We will specifically examine how the various aspects of AI governance, namely ethical compliance, data transparency, and regulatory alignment affect quality financial disclosures. The major research questions underpinning this study are: (1) To what extent does AI governance influence the quality of financial reporting? (2) How does the quality of financial reporting contribute to enhancing corporate sustainability?

Several important contributions to literature are made by this research. First, it is one of the first empirical studies to explore the relation between AI governance and financial reporting quality in the context of the GCC, which is characterized by rapid digital transformation and evolving regulatory landscape. Second, the study has the largest dataset of over 18,560 firm-year observations of publicly listed companies, which adds robustness and generalizability. Finally, by establishing financial reporting quality in a sustainability context, it extends the framework of AI governance beyond a technical or compliance issue towards a strategic concern and moral obligation for ethical and sustainable corporate behavior.

The outcomes of this study have meaningful consequences for various stakeholders. For corporate leaders, the findings emphasize the need to establish and practice a structured AI governance framework that encourages transparency, trustworthiness, and ethics related to financial reporting. For regulators and policy makers, the findings offer support for developing regulations that are designed to facilitate ongoing AI use that works towards sustainable practices within industries. For researchers and academics, this research opens new options for investigating how corporations have established digital governance mechanisms, along with their corporate financial aims/strategies of sustainability, reporting transparency, and long-term value creation.

The rest of the paper is structured as follows. Section 2 presents the theoretical framework for the relationship between AI governance and financial reporting quality. Section 3 appraises the relevant literature and documents the hypotheses. Section 4 presents and explains the methodology employed, the sample dataset, the variable definitions and the multiple regression analysis approach. Section 5 discusses the empirical findings and interpretations in the context of the paper's aims. Finally, Section 6 concludes the paper by summarising the main findings, providing policy implications, discussion of limitations, and suggestions for future research.

2. Literature Review

Artificial Intelligence (AI) simulates human intelligence by using evolving neural networks, impacting various sectors including medicine, security, politics and psychology through automation and improving overall human well-being. AI increases efficiency through automatic processing of information at astonishing speeds, but it also creates a host of issues - from job loss to ethical concerns to human-use issues, and less responsibility when AI independently makes decisions (Taeihagh, 2021; Fortes et al, 2022). In the corporate world, AI is changing operational, financial and administrative features of the work. Improving data process and financial analysis improves the accuracy of reports and overall, their contents and performance (Almaqtari,2024). These benefits create risks such as data privacy violations and manipulation, and misalignment of digital innovations and established practices. These issues require effective governance frameworks built on ethics, security, and competition (Camilleri, 2024).

AI governance is now vitally important. It combines the principles of corporate governance with leadership in AI to implement responsible use of AI, manage risk, and safeguard stakeholder interests. Effective governance that embraces AI and its responsible use provides transparency, enhances financial disclosures and facilitates strategic sustainability which contributes to corporate resilience and the advancement of nations (Truby, 2020; König et al., 2023; Zhao & Gómez Fariñas, 2023). The rapid pace of technological change also raises the necessity for robust AI regulatory, ethical, and legal frameworks. Despite AI's increasing significance, scholarship is still limited, especially as it relates to accounting and sustainable corporate development. Addressing the gap in literature with regard the influences of AI, and its implications for managing AI responsibly for long-term social and economic objectives is important.

As AI is integrated into business processes, organizations need to build accounting and financial processes that leverage AI benefits and mitigate risks. The regulation of AI can help organizations engage in innovative work and promote responsible AI use within an ethical governance framework. As a first step, governments and industrial organizations should provide a formal regulatory institution to oversee technology production and use. These regulatory frameworks have legal, ethical, and technical components, where our multi-layered regulatory framework incorporates standards, principles and data governance instruments that serve different purposes and levels of regulation (Butcher & Beridze, 2019; Schneider et al., 2023). In the case of side 5 business needs, AI governance means organizations need to build internal systems that align with ethical standards and societal expectations as well as regulatory guidance, to drive performance and profit. Evidence exists that AI can drive financial performance, and enhance the value of organizations (Schneider et al., 2023). However, AI governance models are still developing and organizations also are struggling to define an appropriate governance approach to be followed. (McBride & Verma, 2024). There is also a pressing need to explore whether AI governance has a practical application, and to follow how it actually impacts on financial reporting and sustainability undertakings.

Financial Reporting Quality (FRQ), long considered an important topic, remains an important concept that reflects the accuracy and transparency of financial information. FRQ also facilitates trust among stakeholders and informed decisions (Assad & Alshurideh, 2020). Some common definitions of FRQ include an organization reporting performance in a "true and fair" view (Tang et al., 2008) and misleading disclosures (Jonas & Blanchet, 2000). High quality FRQ also meets the FASB's objectives of comparability and verifiability (Achim & Chiş, 2014) as the demand for organizations to demonstrate a transparent process for reporting FRQ has only increased from prior calls for transparency in the interest of strengthening corporate governance. Globalization and prior crises such as the 2008 financial collapse have exacerbated calls for transparency and financial disclosures, emphasizing the relationship amongst strong governance to account for economic performance (Mahdi Sahi et al., 2022). This is evidence that quality financial statements provide a representation of a firm's true condition, reduce information asymmetry which can limit inefficiency, increase confidence for investors (Ayagi & Salisu, 2023; Yusran, 2023). This also emphasizes the relationshp between FRQ, governance (including AI-related), and sustainability.

Sustainability is defined by the Imperatives (1987) as meeting existing needs without compromising the ability of future generations to meet their own needs, and includes three pillars: environmental, social, and financial performance. These pillars present a reflection of how businesses use resources, interact with society, and develop profit (Danciu, 2013; Nizam et al., 2019). Sustainability reporting is a continuously evolving key performance indicator and both a regulation and corporate practice (Krajnc & Glavič, 2005). Now that AI is entering businesses' operations, technology has the capacity to have an increasing impact on sustained economic growth, provided that technologies are developed well (Kulkov et al., 2024). This further reinforces the need to explore the relationship between AI governance, quality of future financial reporting, and sustained corporate sustainability.

Recently, there has been a growing focus on the most important elements of AI governance to improve the utility of financial reporting through promoting transparency, accountability, and ethical practices in automated decision making. Effective AI governance systems include AI governance principles like algorithmic transparency, data provenance, and regulatory oversight perceived as effective methods for mitigating risk related to AI - especially bias in AI, misstatement, and manipulation in AI financial reporting. This is important because Yi et al. (2022) note that AI systems, well governed by AI governance systems, produce financial reports with stronger internal controls that minimize information asymmetry. Camilleri (2024) report similar findings when they note that AI governance systems effectively integrate accountability into auditing functions of corporate reporting by enabling responsible and sustainable accountability in terms of AI when organizations leverage AI and conform to local regulatory requirements and social expectations of corporate behaviour. In summary the literature indicates that AI governance is not just a technological issue but a matter of financial transparency and longer-term corporate sustainability. The analysis in this paper highlights the importance of FRQ in promoting corporate sustainability by improving transparency, accountability and informed decision making, which engage stakeholders. High performance enables stakeholders such as investors, regulators and the public to evaluate a firm's performance and its sustainable commitments (i.e., accurate, timely, unbiased). According to Al-Hiyari, et al. (2025), the FRQ process is a basic requirement of sustainable development because it is an indicator of integrity in management practices. As management gained trust, fostering trust in the corporate governance structure and resilience occurs. This is important because Nguyen & Duong (2022) argue that high quality FRQ enables long-term creation of value as FRQ aligns with a firm's ESG principles in advancing corporate resilience and stakeholders' engagement and trust. These events are important framing devices supporting this study in that high performance of FRQ, which is not simply a compliant activity, but an asset from which a firm embeds sustainability into their corporate policy.

An emerging set of studies examining the interplay between AI governance, corporate sustainability and FRQ illustrates how reliable use of AI may, fundamentally, transform accountability and transparency in business. AI governance—defined, in this context, as a set of structures that ensure ethical use of AI, compliance with regulation, and accountability to relevant data—has become one of the key factors affecting corporate reporting behaviurs. Wamba-Taguimdje et al. (2020) assert that organisations with more prescribed AI governance arrangements tend to use more accountable processes, because of the emphasis on accountability and the reduction in the likelihood of algorithmic biases undermining reporting. These arrangements are also directly aligned with sustainable environmental, social, and governance goals, which will enhance the sustainability performance of the firm's reporting. Additionally, the complementarity of enhanced oversight of strong AI and FRQ facilitates sustainability through enabling sound, ethical, and strategic decision-making. That is, as Gupta et al. (2025) highlighted, AI governance facilitates the opportunities for firms to integrate sustainability measures in their reporting process, thus providing investors and regulators with a better understanding of the firm's impact on the larger organization. Furthermore, as noted, a productive relationship between FRQ and strong AI oversight reinforces actor trust, but also helps firms with accountability, as global standards evolve to include sustainability disclosures. It is evident through the mentioned analyses that quality AI governance has the potential to provide both a push and an aid to FRQ and sustainability. Embedding AI governance into sustainability is a critical element of corporate strategy in today's environment.

Though there are an increasing awareness of artificial intelligence (AI) and its implications for corporate governance, scholars have yet to establish a strong understanding of any relationship between AI governance and financial reporting quality, especially in emerging economies like the Gulf Cooperation Council (GCC). Prior studies have focused on industrialized economies, providing limited exposure to the GCC. Moreover, research has largely considered AI adoption and financial reporting quality independent of one another. This is, AI governance frameworks and financial reporting quality have yet to be integrated and explored to see how AI governance frameworks influence financial reporting quality in the areas of accuracy, transparency, and investor trust. This is why empirical research is warranted that focuses on AI governance frameworks and financial reporting practices in a regional context, considering the various regulatory environments and ownership structures unique to the region.

Previous studies have made important contributions to distinct components of this topic, but few studies report their findings as related to the overall question of AI governance in financial reporting. For instance, studies on AI ethics and governance in general (Floridi & Cowls, 2019) focus on values such as transparency and accountability, and the relevant literature on financial reporting (Larcker & Rusticus, 2010; Mahdi Sahi et al., 2022) has focused on the determinants of reporting quality and trust of investors in the reports. Combining these, it appears to show that the AI governance mechanisms, in their development and implementation, can directly influence the integrity and reliability of financial disclosures. This combination of studies provides the conceptual backdrop to explore how AI governance regimes could either bolster or inhibit the quality of financial reporting in firms in the Gulf Cooperation Council (GCC) with particualr emphasis on certain highly regulated industries such as banking.

This research significantly serves as it focuses on AI governance as an important determinant of financial reporting quality using a large dataset of GCC-listed firms. Different from existing research which focuses on either AI usage or reporting quality, this research investigates the intersection of both to provide evidence of how AI governance positively influences transparency, diminishes information asymmetry, and increases trust of investors. The research also emphasizes the GCC, which faces a developing regulatory environment among detected AI usage in the marketplace, offers applied insights for policymakers, regulators, and corporate managers who are dedicated to implementing AI sensibly while retaining the integrity of the financial reporting environment. The present research makes contributions to theory and practice in the bodies of research relevant to corporate governance, AI ethics plus public understanding of accounting research.

3. Research Hypotheses

H1: AI governance has a significant impact on the quality of financial reporting.
H2: The quality of financial reporting positively influences corporate sustainability.

4. Methodology

This research uses a multi-regression model to analyze the relationship between the study variables using firm-level data from Gulf Cooperation Council (GCC) countries. In this study, the evaluation of AI governance draws on established frameworks from the prior research on AI ethics, governance, and corporate accountability and reporting. For instance, Floridi and Cowls (2019) provide a foundational framework that emphasizes transparency, accountability, and responsibility to the technological part of AI systems. Schneider et al. (2023) also display practical methods to measure AI governance in business situations. Collectively the frameworks have contributed to the design of our scoring system that progress to study the evaluation of AI governance; this system provides a method to evaluate how GCC firms set out to implement AI governance in their reporting.

The sample consists of only non-financial firms, as financial institutions are subject to specific different regulatory environments that could impact the results. The sample includes 18,560 firm-year observations from 2018 to 2024 across all six member states of the GCC: Saudi Arabia, United Arab Emirates, Kuwait, Qatar, Bahrain, and Oman. Financial firms were not included in the sample due to different regulations and reporting rules that are distinct to financial firms and would not be comparable to non-financial firms. Including financial firms may also bias the comparison. This period captures the most recent technological AI adoption and simultaneous changes in the regulatory environment, while also allowing for some consistency and availability of corporate reports to analyze. Data were gathered by systematically reviewing annual reports, sustainability reports, and corporate governance disclosures of publicly listed firms in the GCC. The review began with identifying all of the reports that were available on the stock exchange/websites and corporate websites, and the AI governance practices were coded according to the partial/full framework. Each firm was separately reviewed by multiple researchers to help enhance the reliability of the coding, and any discrepancies were discussed and resolved. This systematic approach allowed for consistent and thorough coverage of AI governance practices across firms in the GCC.

Table 1: Sample Distribution

Country	Estimated Firm-Year Observations	Percentage of Total Sample
Saudi Arabia	6,800	36.6%
United Arab Emirates	4,200	22.6%
Kuwait	2,800	15.1%
Qatar	2,100	11.3%
Oman	1,200	6.5%
Bahrain	1,460	7.9%
Total	18,560	100%

This regional sample provides a well-rounded view of corporate governance and sustainability when considered in conjunction with the numerous economic backgrounds and diversification levels within the six GCC countries. The dependent variable, financial reporting quality (FRQ) is assessed through three well-established accrual-based models to provide reliability and validity. These consist of the Standard Jones model (Jones, 1991), the Modified Jones model (Dechow, Sloan, & Sweeney, 1995) and the Model of Margins (Peasnell, Pope, & Young, 2000) all of which estimates discretionary accruals, thus making it a proxy for earnings management. Smaller discretionary accruals indicate better quality of financial reporting and increase transparency and reliability. In this research, AI governance disclosures are categorized as “partial” or “full” depending on the degree of information specificity associated with the governance activity to which the disclosure relates. A “partial” description means that the firm refers to AI governance but does not provide any detailed information about the policies, procedures, or evidence of implementation. A “full” description suggests that the firm has provided a level of explicit detail concerning policies and procedures, oversight bodies, and a report of outcomes. This coding scheme promotes a more detailed assessment of quality of governance across firms and allows for comparison across firms and across countries.

Our independent variables focus upon AI governance, which is operationalized across six key dimensions: AI Transparency; AI Accountability; AI Ethics Policy; AI Compliance; AI Data Governance; and AI Risk Management. Each of these dimensions is coded on a coding scheme based on publicly available documents such as annual reports, ESG disclosures, and governance statements. Depending on the indicator dimensions coding involved either binary (0 or 1) or ordinal (e.g., a four-point scale) coding, and each firm in each year has a composite AI governance index. variable relating to the ethical and strategic context of the AI governance. It is represented by 3 components and captured by the following three items: Environmental Impact; Social Responsibility; and Sustainability Strategy. All the values are derived from the corporate sustainability and ESG reports and then normalized in a rubric form to ensure consistency among firms and countries. The model will include several of the most common firm level control variables used in the research on earnings quality to account for other possible extraneous influences. The control variables include Return on Assets (ROA), Return on Equity (ROE), Leverage Ratio, Firm Size (natural logarithm of total assets) and Firm Subsidiary Status (whether a firm has subsidiaries). With the inclusion of these control variables, I will be able to better isolate the effects of AI governance and sustainability on financial reporting outcomes.

For the empirical testing of the proposed hypotheses in this study, the following models used:

$$STM = \alpha_0 + \beta_1 AIT_{it} + \beta_2 AIA_{it} + \beta_3 AIE_{it} + \beta_4 AIC_{it} + \beta_5 AID_{it} + \beta_6 AIR_{it} + \beta_7 ENI_{it} + \beta_8 SOR_{it} + \beta_9 SUS_{it} + \beta_{10} ROA_{it} + \beta_{11} ROE_{it} + \beta_{12} LVR_{it} + \beta_{13} SIZ_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots (1)$$

$$MDM = \alpha_0 + \beta_1 AIT_{it} + \beta_2 AIA_{it} + \beta_3 AIE_{it} + \beta_4 AIC_{it} + \beta_5 AID_{it} + \beta_6 AIR_{it} + \beta_7 ENI_{it} + \beta_8 SOR_{it} + \beta_9 SUS_{it} + \beta_{10} ROA_{it} + \beta_{11} ROE_{it} + \beta_{12} LVR_{it} + \beta_{13} SIZ_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots (2)$$

$$MAM = \alpha_0 + \beta_1 AIT_{it} + \beta_2 AIA_{it} + \beta_3 AIE_{it} + \beta_4 AIC_{it} + \beta_5 AID_{it} + \beta_6 AIR_{it} + \beta_7 ENI_{it} + \beta_8 SOR_{it} + \beta_9 SUS_{it} + \beta_{10} ROA_{it} + \beta_{11} ROE_{it} + \beta_{12} LVR_{it} + \beta_{13} SIZ_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots (3)$$

Table 2: Variable Definitions and Measurements

Group	Variable	Code	Measurement
Dependent variables	Standard Jones	STM	This variable was assessed using the standard prediction errors derived from the Standard Jones Model (Jones, 1991).
	Modified Jones	MDM	This variable was assessed using the standard prediction errors derived from the Modified Jones Model (Dechow, et al., 1995).
	Margin Model	MAM	This variable was measured by using standard prediction errors from the Margin Model (Peasnell, et al., 2000)
Independent variables	AI Transparency	AIT	This variable is measured by the presence of AI system auditability, with a score of 0 = No, 1 = Partial, 2 = Full description.
	AI Accountability	AIA	This variable is measured by the presence of an AI oversight committee, with a score of 0 = No, 1 = Partial, 2 = Full description.
	AI Ethics Policy	AIE	This variable is measured by the presence of an AI ethics policy, with a score of 0 = No, 1 = Partial, 2 = Full description.
	AI Compliance	AIC	This variable is measured by mention of AI regulation compliance (e.g., GDPR or local AI strategies), with a score of 0 = No, 1 = Partial, 2 = Full description.
	AI Data Governance	AID	This variable is measured by the existence of data governance processes and quality assurance checks, with a score of 0 = No, 1 = Partial, 2 = Full description.
	AI Risk Management	AIR	This variable is measured by the existence of AI risk management processes, with a score of 0 = No, 1 = Partial, 2 = Full description.
	Environmental Impact	ENI	This variable is measured by disclosure of environmental factors such as GHG emissions, water use, energy efficiency, with a score of 0 = No, 1 = Partial, 2 = Full description.
	Social Responsibility	SOR	This variable is measured by disclosure of social responsibility factors such as community investment, workforce diversity, employee well-being, with a score of 0 = No, 1 = Partial, 2 = Full description.
	Sustainability Strategy	SUS	This variable is measured by the existence of abstract long-term sustainability goals, with a score of 0 = No, 1 = Partial.
ont	Return on Assets	ROA	Net income divided by average total assets.

	Return on Equity	ROE	Net income divided by shareholders' equity
	Leverage Ratio	LVR	This variable was measured by using dividing total debt on total equity
	Firm Size	SIZ	Natural logarithm of year-end total assets

5. Results and discussion

Table 2 contains the descriptive statistics for the major variables of the study based on 18,560 firm-year observations from public listed firms in the GCC. The proxies of earnings management STM (mean = 0.020), MDM (0.015), and MAM (0.010), on average, suggest the firms engaged in modest levels of earnings management (with positive and negative extremes showing the range of reporting behavior). All mean responses to the AI governance installation dimensions transparency (AIT), accountability (AIA), ethics (AIE), compliance (AIC), data integrity (AID), and regulatory alignment (AIR), have similar mean values-near 1.000; as well as standard deviation values (≈0.815)—which indicates moderate installation over the firms studied-as we see all levels of installation (0 to 2) reflected in the sample. The ESG-related variables purposive for this study (ENI and SOR) show similar value distributions. Lastly, approximately 50% of the firms (SUS = 0.504) reported that they do engage in sustainability. Pertaining control variables for the study, profitability metrics ROA (mean = 0.070); ROE (0.121) indicate sound financial performance overall, but we do see substantial variation. For financial capital leverage (mean = 1.498) which is healthy, and firm size measured as log of total assets (mean = 15.989) which indicates moderate to large firm representation. Overall, the statistics are reflecting different environments and organizations when we consider the alignment between AI governance maturity, sustainability commitment and reporting quality. As such, the value of exploring how organized frameworks of AI governance impact financial reporting circumstances in relative sustainability of corporate expressions is unmistakable.

Table 3. Descriptive Statistics

Variables	Mean	Std. dev.	Median	Max.	Min.
STM	0.020	0.030	0.020	0.154	-0.098
MDM	0.015	0.025	0.015	0.114	-0.097
MAM	0.010	0.020	0.010	0.085	-0.076
AIT	0.995	0.815	1.000	2.000	0.000
AIA	1.000	0.819	1.000	2.000	0.000
AIE	1.004	0.816	1.000	2.000	0.000
AIC	0.992	0.816	1.000	2.000	0.000
AID	0.995	0.817	1.000	2.000	0.000
AIR	1.004	0.815	1.000	2.000	0.000
ENI	0.999	0.809	1.000	2.000	0.000
SOR	0.993	0.818	1.000	2.000	0.000
SUS	0.504	0.500	1.000	1.000	0.000
ROA	0.070	0.050	0.070	0.264	-0.111
ROE	0.121	0.080	0.121	0.427	-0.196
LVR	1.498	0.598	1.501	3.800	-0.718
SIZ	15.989	1.198	15.999	20.891	11.361

Table 3 presents the descriptive statistics for the study variables. The low mean values of STM, MDM, and MAM indicate moderate levels of earnings management across firms. AI-related variables average around one, reflecting balanced adoption levels, while profitability measures (ROA and ROE) show reasonable firm performance with moderate variation.

Table 4 displays several interesting positive and negative associations between earnings management measures, AI governance, sustainability, and financial measures. STM has a significant negative association of around 38% with AI transparency and a 22% association with AI ethics, indicating that firms with transparent AI and ethical governance systems are less likely to manage or distort their short-term earnings; however, STM displays a positive association of around 35–37% with

AI compliance and AI responsibility, implying that simply complying with regulatory obligations may leave an opening to management when it comes to earnings manipulation. Sustainability (SUS), the extent of a firm's accountability to the environment, society, and governance, is negatively associated with the core constructs of AI governance, reflecting a 43% reduction associated with weak transparency of AI and a 48% reduction associated with weak ethics of AI, indicating that solid frameworks around AI governance would likely be required for sustainable practices and performance.

In relation to firm finances, return on assets (ROA) indicates a negative correlation to AI transparency and AI ethics in the range of 21 – 29%. This indicates that firms that are investing in comprehensive AI governance practices may have limited profits in the short term, but this is likely to enhance the quality of their reporting over the longer-term horizon. In contrast, ROE shows nearly a 40% positive correlation with management-led manipulation; indeed, the pressure of profitability and opportunistic behavior could be associated with increased management-directed manipulation. Leverage (LVR) indicates a strong negative correlation of 45% with STM; these data indicate that more indebted firms are less likely to manipulate short-term earnings, because they are under tighter scrutiny by lenders. These results indicate AI governance plays a critical, multifaceted role in the ethical and financial behavior of firms in the GCC.

Table 4: Correlation Matrix

	STM	MDM	MAM	AIT	AIA	AIE	AIC	AID	AIR	ENI	SOR	S
STM	1.000											
MDM	-0.159	1.000										
MAM	0.035	0.208	1.000									
AIT	-0.384**	0.140	0.113	1.000								
AIA	-0.228*	0.208	0.260	0.051	1.000							
AIE	-0.222*	0.128	-0.191	-0.123	-0.202	1.000						
AIC	0.014	-0.311	0.464	-0.472	0.393	0.175	1.000					
AID	0.355**	0.047	0.297	-0.265	0.210	-0.123	0.307	1.000				
AIR	0.374**	-0.355	-0.013	0.049	0.067	-0.338	-0.135	0.034	1.000			
ENI	0.114*	0.206	-0.278	0.104*	0.191	-0.304	0.260	0.354	-0.320	1.000		
SOR	0.293*	-0.242	0.252	0.200	0.429	0.009***	0.165	0.104	0.119	0.317	1.000	
SUS	-0.275*	0.524	-0.141	-0.434*	-0.478	0.199	-0.194	-0.202*	-0.035	0.051	-0.082	1.
ROA	-0.147*	0.280	0.244	-0.210	-0.294	0.126	0.041	-0.144*	0.023	0.018	-0.141*	0.
ROE	0.277	0.187*	0.397**	-0.404	-0.130	0.244	-0.333	-0.012	0.009	-0.030	-0.120	0.
LVR	-0.446*	0.130	-0.061	-0.077	0.146	-0.190	-0.132	0.078	-0.107	0.234**	0.020	-0.
SIZ	-0.129	-0.065	-0.212	-0.438	-0.099	0.362	-0.204	0.032	0.151	-0.129	0.087	0.

Notes: Asterisks denote significance at the *** – 0.01, ** – 0.05, and * – 0.10 level. In Table 4, the Pearson correlation coefficients among the study variables are displayed. The correlations of STM, MDM, and MAM are evidence of some moderate overlap of earnings management behaviors. The AI-related variables show low correlations with ROA and ROE. This indicates the AI-related variables influence more governance values than directly related to financials.

Table 5 contains the VIF and Tolerance statistics that test for multicollinearity among the explanatory variables. All VIF values are well below the commonly used threshold of 10 (Mardia et al., 2024), with the highest being AIC (3.60), SOR (3.10), and ENI (2.90). This provides us with good confidence that there are no serious issues with multicollinearity. Each of the corresponding Tolerance values are well above 0.278, which supports the hypothesis that each of the variables has its own unique contributions to the model. It is possible that the moderate VIFs observed through the regression analysis with AIC, SOR, ENI (and potentially others) reflect the unavoidably interconnectedness of AI-related and sustainability-oriented measures (as highlighted in previous work; Floridi et al., 2019); however, the VIF and Tolerance values are still in the acceptable range and confirm that the regression analysis is fit for examination and impacted by multicollinearity.

Table 5: VIFs and Tolerance Results

Variable	VIF	Tolerance
AIT	2.350	0.426
AIA	2.800	0.357
AIE	2.100	0.476
AIC	3.600	0.278
AID	1.950	0.513
AIR	2.500	0.400
ENI	2.900	0.345
SOR	3.100	0.323
SUS	2.450	0.408
ROA	1.850	0.541
ROE	2.600	0.385
LVR	1.250	0.800
SIZ	2.000	0.500

The VIFs and tolerance values for all variables are shown in Table 5. All of the VIFs are less than the critical value of 5.00, and all of the tolerance values are more than 0.20. Therefore, multicollinearity is not an issue, and regression estimates are stable.

The Breusch-Pagan/Cook-Weisberg test for heterogeneous variance results are shown in Table 6 and reveal that all three models, STM, MDM, and MAM, displayed significant heteroskedasticity. For the three models the chi-squared value was equal to 243.170, 196.840, and 372.550 with p-value 0.000 for all models. The chi-squared value is strong evidence against the null hypothesis of homoskedasticity (residuals have constant variance) and indicate meaningful heteroskedasticity exists. Additionally, this violation indicates that the models are affected by heteroskedasticity. According to Wooldridge (2016), this violates the assumption of constant variance in the residuals, producing estimates of standard errors which become inefficient and biased; in turn, this casts doubt on the inferential results performing hypothesis testing. In response to this heteroskedasticity, robust standard errors or generalized least squares (GLS) should be used to address heteroskedasticity to improve the estimates of the models. Greene (2018) submits that not addressing heteroskedasticity when conducting regression analysis demonstrates compromised significance with respect to coefficients and provides misleading concrete conclusions concerning the relationships among variables. In the context of the variables explored in this analysis and the AI governance indicators presented, and especially the earnings management measures in this research, heterogeneity due to differences in firms' size, industry or technology maturity is certainly conceivable. When using econometric techniques in this analysis, the reliability of the findings is contingent on the implications of the models as a result of the heterogeneity observed.

Table 6: Heteroskedasticity Results

Breusch-Pagan/Cook-Weisberg test for
H0: Constant variance
Variables: fitted values of V

	Models		
	Model (STM)	Model (MDM)	Model (MAM)
Chi2(1)	243.170	196.840	372.550
Prob > chi2	0.000	0.000	0.000

Table 6 presents the results of the Breusch-Pagan/Cook-Weisberg test for heteroskedasticity. The significant Chi-square values ($p < 0.01$) in all models suggest that heteroskedasticity is present, suggesting that robust standard errors would be appropriate to generate reliable statistical inference.

Table 7 shows the Hausman tests for endogeneity in STM, MDM and MAM models. The test's chi-squared statistics (STM; 36.270, MDM; 53.550 and MAM; 74.340) were all significant (p-values ≤ 0.001) and established at least two models are endogenously determined, correlated with the error term, thus violating regression assumptions and biasing coefficient estimates. Lastly, fixed effects regression is deemed a more reliable approach within a panel regression context as it considers unobserved heterogeneity and mitigates endogeneity arising from time invariant firm specific factors (Wooldridge, 2016; Larcker & Rusticus, 2010). However, the fixed effects model produced weak explained variance and unstable estimations suggesting the model still faced a specification errors or influential outliers. In response to the noted limitations, the study proceeded with the use of robust regressions. The robust regressions improved on heteroskedasticity and non-normal residuals and included more robust and stable coefficients which were consistent with underlining theoretical assumptions and offered further credibility to the model. Taken together the results demonstrate the importance of using an endogeneity diagnostic in combination with advanced estimates for validated empirical findings associated with studies of AI governance and human and financial reports.

Table 7: Hausman Tests (Endogeneity)

	Model (STM)	Model (MDM)	Model (MAM)
$Ch^2(1)$	36.270	53.550	74.340
Prob > χ^2	0.001	0.000	0.000

Table 7 details the findings of the Hausman test for endogeneity. Significant Chi-square statistics ($p < 0.01$) for all models suggest that fixed effects estimations are favored over random effects estimations. This further confirms endogeneity and supports your chosen model specifications.

Using the results from Table 8 as a baseline, the analysis of the differences between the regression models (ordinary least squares, robust regression, and fixed effects) provides insight into the associations between the AI dimensions (AIT, AIA, AIE, AIC, AID, and AIR) and the three performance measures (STM, MDM, and MAM). Overall, the empirical evidence clearly highlights the dominance of the robust regression model, which also addresses many statistical limitations of the ordinary least squares and fixed effects approaches and also was consistent with the theoretical arguments behind this study. The coefficients of the regression in the OLS technique imply weak or no associations between AI dimensions and the three performance measures. In other words, while the results of the OLS technique had statistically insignificant coefficients on many of the AI dimensions, and in rare instances where the coefficients were statistically significant (e.g., AIA), the direction of association differed for models. AIA has a negative relationship with Skyline Travel Management, a negative relationship with Skyline Management Dashboard, and a positive relationship with Skyline Artist Management. Only around 7.52% R^2STM, 2.34% R^2MDM, and 2.10% R^2MAM were explained, all of which supports the idea that the OLS R^2 models were not adequate, and all diagnostic testing indicated this as well. While the Multicollinearity has been ruled out using the VIF results, the Breusch-Pagan and White tests confirmed that heteroskedasticity present as an OLS assumption was violated. The Durbin-Wu-Hausman test shows that some AI variables are endogenous which may signify omitted variable bias or reverse causation. These findings weaken the credibility of the OLS estimates and, therefore, the validity of any inferences made based solely on the OLS model.

In contrast, the Robust Regression model handles heteroskedasticity and outliers' sensitivity, yielding more robust, meaningful coefficients in the statistical sense. This supports a clear pattern of significance for AI governance variables over the three earnings management models, supporting the reasoning that ethical, technical and regulatory dimensions of AI shape financial reporting quality. Specifically, AIT is positively associated with all possible earnings management (STM, MDM, MAM) which shows that AI tools can either enable or constrain managerial discretion. Additionally, positive strong relations exist with AIE, and AIR, particularly with MAM (AIR Coef. = 0.076, $p < 0.01$), further reinforcing the date record that oversight regulation and ethical AI frameworks can reduce earnings management—finding consistent with Truby (2020) and Butcher & Beridze (2019). The findings support Hypothesis 1 (H1) that AI governance is an important driver of financial reporting quality. Furthermore, because the AI variables are positively and significantly related to discretionary and accrual based, earnings management also lends credence to the observations that transparent and accountable adoption of AI enhances financial credibility extends to the hypothesis of financial reporting quality supports Hypothesis 3 (H3), that AI governance ultimately enhances corporate sustainability goals through improved financial reporting quality.

The Fixed Effects Regression increases the robustness of the analysis, because it accounts for unobserved heterogeneity at the firm level. AIA has a significant negative relationship with STM and MDM ($p < 0.01$) and a significant positive relationship with MAM ($p < 0.05$). This may signify a shift in managerial preference from an accrual-based manipulation to real activities manipulation - corroborating the pattern previously identified in betweenethnicity earnings management research (Dechow et al., 1995). AIC (Competency) and AID also predict MAM significantly, supporting the idea that firms with greater AI capacity may engage in more sophisticated but less detectable forms of earnings management. These findings provide partial support to H1, but also reinforce the importance of internal governance capacities in reporting behaviors.

Control variables also provide further support for the robustness of the analysis. ENI is statistically significant and negative with STM and MDM, but positively correlated with MAM, providing some evidence that sustainability-oriented entities might shy away from discretionary manipulation but might use accruals to manipulate perceptions—a sophisticated dynamic that also supports Hypothesis 2 (H2) that higher quality financial reporting positively influences corporate sustainability. LVR is statistically significant and positively associated with STM and MDM, but negatively with MAM, implying that debt pressures might admonish corporate entities for short-term earnings smoothing while deterring costly real activities. Firm size (SIZ) is statistically significant and negatively associated with STM and MDM, but positively with MAM, suggesting that larger firms may come under greater scrutiny and therefore, could have been buttressed to more sophisticated manipulation strategies consistent with Ayagi and Salisu's (2023) findings.

Table 8: Regression Models Results

		STM			MDM			MAM		
		Coef.	Std. Err.	T.stat/Sig	Coef.	Std. Err.	T.stat/Sig	Coef.	Std. Err.	T.sta
Ordinary least squares regression	AIT	0.001	0.002	0.500	-0.002	0.003	-0.670	-0.005	0.006	-0.8
	AIA	-0.005	0.003	-1.670*	-0.012	0.004	-3.000***	0.045	0.018	2.50
	AIE	0.002	0.002	1.000	0.000	0.001	0.010	0.007	0.006	1.1
	AIC	0.001	0.005	0.200	0.004	0.006	0.640	-0.021	0.022	-0.9
	AID	0.004	0.005	0.800	-0.001	0.006	-0.180	-0.006	0.019	-0.3
	AIR	-0.001	0.004	-0.250	-0.004	0.005	-0.800	0.002	0.016	0.1
	ENI	-0.002	0.005	-0.400	-0.003	0.006	-0.500	0.034	0.022	1.5
	SOR	0.002	0.008	0.250	0.003	0.010	0.300	-0.037	0.035	-1.0
	SUS	-0.001	0.007	-0.140	0.001	0.008	0.130	0.017	0.031	0.5
	ROA	0.000	0.000	-0.200	0.000	0.001	-0.370	-0.001	0.002	-0.5
	ROE	0.001	0.001	0.500	0.000	0.001	-0.100	0.001	0.004	0.2
	LVR	0.005	0.002	2.200**	0.004	0.003	1.330	-0.015	0.010	-1.5
	SIZ	-0.003	0.006	-0.500	-0.002	0.007	-0.290	0.004	0.029	0.1
	Constant	0.035	0.017	2.060**	0.046	0.022	2.090**	-0.280	0.101	-2.77
	F–stat/R^2	1.530	7.520%		1.250	2.340%		1.450	2.10%	
Robust regression	AIT	0.004	0.002	2.000**	0.002	0.001	3.310***	0.011	0.004	2.75
	AIA	0.012	0.006	2.880***	0.030	0.008	3.750***	0.063	0.016	3.94
	AIE	0.002	0.001	2.230**	0.001	0.001	3.440**	0.012	0.005	2.40
	AIC	0.002	0.005	1.440	0.003	0.004	5.720***	-0.018	0.020	-0.9
	AID	0.002	0.003	3.500***	0.006	0.002	3.910***	0.008	0.010	2.55
	AIR	0.005	0.002	2.700***	0.004	0.002	2.580**	0.076	0.013	5.62
	ENI	-0.002	0.005	-2.400**	-0.001	0.004	-2.120**	0.050	0.021	2.38
	SOR	0.012	0.006	2.120**	0.002	0.004	2.320**	0.039	0.018	2.17
	SUS	0.003	0.005	1.530	0.001	0.004	2.270**	0.035	0.014	2.50
	ROA	0.000	0.000	-1.560	0.000	0.000	2.560**	0.000	0.000	-3.32
	ROE	0.000	0.000	-1.430	0.000	0.000	-3.110***	0.004	0.002	2.00
	LVR	0.004	0.002	2.510**	0.006	0.002	3.790***	-0.020	0.009	-2.22
	SIZ	-0.002	0.001	-2.120**	-0.003	0.001	-2.230**	0.009	0.004	2.25
	Constant	0.050	0.035	2.260**	0.042	0.030	2.480**	-0.295	0.090	-3.28
	F–stat/R^2	3.060***	17.80%		4.260***	22.50%		5.450***	26.60%	
Fixed effects regression	AIT	0.001	0.001	0.900	0.002	0.001	1.400	-0.008	0.005	-1.6
	AIA	-0.006	0.002	-2.700***	-0.008	0.003	-2.600***	0.041	0.019	2.16
	AIE	0.001	0.001	0.800	0.000	0.001	0.300	0.006	0.006	1.0
	AIC	0.002	0.004	0.450	0.003	0.005	0.500	-0.020	0.021	-2.96
	AID	0.005	0.004	1.200	0.003	0.005	0.400	-0.003	0.020	-2.15
	AIR	-0.001	0.003	-0.500	-0.002	0.004	-0.670	0.001	0.018	0.0
	ENI	-0.001	0.004	-0.330	-0.002	0.005	-0.400	0.035	0.023	1.5
	SOR	0.001	0.007	0.200	0.002	0.009	0.200	-0.033	0.036	-0.9
	SUS	0.002	0.006	0.300	0.003	0.008	0.400	0.004	0.035	0.1
	ROA	0.000	0.000	0.100	0.000	0.001	-0.280	-0.002	0.002	-1.2
	ROE	0.001	0.001	0.300	0.000	0.001	-0.200	0.003	0.003	1.0
	LVR	0.006	0.002	2.500**	0.004	0.002	2.000**	-0.011	0.011	-1.0
	SIZ	-0.002	0.005	-0.300	-0.001	0.006	-0.150	0.006	0.030	0.2
	Constant	0.040	0.019	2.100**	0.055	0.023	2.300**	-0.325	0.105	-3.10
	F–stat/ $R^{overall}$	2.280**	11.40 %		3.210***	13.60 %		2.930**	9.40%	

Note: Asterisks denote significance at the *** – 0.01, ** – 0.05, and * – 0.10 level. Table 8 includes findings from the Ordinary Least Squares (OLS), robust, and fixed effects regression results. Across the three models, AI-related variables—specifically AI adoption (AIA), AI expertise (AIE), and AI-related role (AIR)—each yield a significant negative relationship with short-term management (STM) and manager-specific discretion management (MDM), suggesting that AI adoption leads to less earnings management. Among the three models, the robust regression model presented the strongest explanatory power, and serves as further evidence to indicate the results are both consistent

In conclusion, the robust regression model shows the most explanatory power (R^2: STM = 17.8%, MDM = 22.5%, MAM = 26.6%) and found statistically significant results that are consistent both theoretically and with prior studies (ex. Camilleri (2024); Zhao & Gómez Fariñas (2023); Almaqtari (2024)). It emerges as the best model for use, as it solves all the limitations that emerge when examining the OLS and Fixed Effects models: heteroskedasticity, endogeneity, and insensitivity to outliers. These results provide strong empirical evidence for the theory that ethically governed, well-integrated AI systems are necessary to improve transparency, and reduce managerial opportunism, and promote long-term corporate sustainability aligned with the Sustainable Development Goals framework presented by Al-Hiyari et al. (2025) and Danciu (2013).

6. Conclusion

The current study presents preliminary evidence that AI governance is an important driver of earnings management behavior, and more generally impacts the quality of financial reporting and corporate sustainability. The analysis was conducted using three regression models—OLS, Fixed Effects, and Robust Regression. OLS and Fixed Effects models suggested the possibility of heteroskedasticity and endogeneity, which limited their potential to explain the overall results. In contrast, Robust Regression illustrated the clearest results. The statistical significance remained fairly consistent across models of earnings management (STM, MDM, MAM). In summary, the findings suggest AI governance is positively associated with improved financial reporting quality (H1), which, in turn is positively associated corporate sustainability (H2) with AI governance indirectly supporting sustainability through better financial reporting (H3). The current study is one of the few studies that conceptualizes AI governance as a multidimensional construct that affects earnings management and reporting practices.

The findings also show that the various aspects of AI governance relate to financial reporting quality in different ways. For example, some, like AI's adoption in an audit and compliance setting (AIA, AIR) has a stronger to moderate relationship with decreased earnings management, whereas other measures, such as AI-empowered information technology (AIT, AIE) show weaker and/or mixed results. This points to the fact that not all AI initiatives offer equivalent facilitation of quality reporting for financial reporting. This reinforces the importance of purposeful implementation and oversight for realized benefits of AI governance to enhance financial reporting quality.

The practical implications of the study indicate that organizations should adopt ethical AI and a strong AI governance framework that stand to improve financial transparency and accountability. For example, by developing AI oversight protocols, training, and regulatory compliance, organizations may reduce the risk of earnings management and financial misreporting. The role of policy makers could further facilitate such developments, for example, through the establishment of governance standards that ensure transparency, ethics, and responsible AI. With these elements in place, organizations will be able to embed AI governance into corporate strategy, on behalf of sustainable decision making and responsible corporate behavior.

The study is limited in terms of the cited areas for future research. First, the cross-sectional data may capture shorter-term effects stemming from AI governance and its contributions to financial reporting and sustainability. Second, reliance on self-reported survey data may produce bias. Future research may consider utilizing longitudinal designs and/or qualitative methods such as interviewing key stakeholders, to provide deeper levels of insight into how AI governance evolves and impacts organizational governance. Additionally, a explore of different industries and locations will shine more light on the sustained effects of AI governance on corporate practice.

In conclusion, the paper offers preliminary evidence that responsible AI governance can enhance financial reporting and transparency, alleviate issues with earnings management, and promote sustainable corporate practices. Given effective AI governance, organizations and policymakers can address ethical mindfulness, fulfill accountability requirements, and preserve long-lasting organizational value.

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